Mixed Traffic and Automated Highways

Chuck Thorpe
Robotics Institute
Carnegie Mellon University

Abstract

A major issue in building a prototype Automated Highway System (AHS) is whether the system needs dedicated lanes, occupied only by computer-controlled cars that communicate and cooperate with each other; or whether the automated vehicles can be provided with enough sensing and intelligence that they can safely operate on regular highways, intermixed with manually-driven vehicles. A major portion of the CMU research effort AHS is focused on determining the technical feasibility of operation in mixed traffic. This paper outlines the issues of mixed traffic vs. dedicated lanes, then describes CMU efforts in building complete demonstration systems, vehicle sensors, obstacle sensors, car tracking software, reasoning for tactical driving, and deployment scenarios.

Mixed Traffic vs. Dedicated Lanes

The National Automated Highway Systems Consortium (NAHSC) is embarked on a seven-year project to build a prototype automated highway. The goal is to develop the specifications for a system that will allow completely hands-off and feet-off automated driving of specially-equipped cars, trucks, and busses, operating on specially-equipped lanes of high-speed limited-access roads. The AHS user will drive the vehicle normally on surface streets to the AHS entrance ramp, indicate a destination, then turn control over to the automated system, which will handle the driving until the right exit is reached. Partners in the NAHSC come from a wide variety of disciplines, in order to cover the range of issues involved in AHS development: vehicle manufacturers (GM), vehicle electronics (Delco), infrastructure design and build (Bechtel and Parsons Brinkerhoff), highway operations (Caltrans), systems integration (Hughes and Lockheed Martin), federal government (USDOT), and research (the PATH consortium centered at Berkeley and CMU).

We are in the middle of many important and interesting design studies. How should we handle obstacles: detect them with onboard sensors; or detect them with sensors built into the roadway; or build strong fences and exclude all foreign objects? Should automated vehicles platoon together, in tightly-linked groups of 10 vehicles, or should they only run as free agents, separated by 10 to 30 meters? What is the role of the driver: passive passenger, who will probably become complacent and distracted and therefore unavailable to help the automated driving system; or careful observer, able to spot subtle signs of potential obstacles?

Of all the design questions, perhaps the most interesting from a robotics viewpoint is whether the system should require dedicated lanes, or should allow mixed traffic. The "dedicated lanes" approach means that vehicles will be allowed to operate under automated control only when in special lanes, physically separated from all manually-driven vehicles. The "mixed traffic" approach means that vehicles will be so capable of sensing and reacting to other vehicles, that they will be able to operate on freeways mixed in with human drivers.

The consortium as a whole is undertaking several studies to analyze the mixed and dedicated options separately, and then to compare the possibilities. At a high level, the discussion comes down to economics vs. technical feasibility. It is probably technically easier to build a dedicated lane facility. All the automated vehicles can be in communication with one another, running at the same speed, cooperating when a vehicle needs to change lanes, and sharing information about detected obstacles. But having a dedicated lane facility requires building one; and there is a chicken-and-egg problem of who will build the lanes before cars are available to use them; and who will buy the cars unless there are lanes on which they can run?

Proc. IROS 97 0-7803-4119-8/97/$10©1997 IEEE

The mixed traffic option, on the other hand, would allow for relatively easy use of the entire network of freeways in the US. Some minor infrastructure may need to be added, depending on the technology used for lateral guidance, but at much lower financial cost than building new lanes, and probably at lower political cost than converting existing lanes for the sole use of automated vehicles. Individuals who purchase a specially-equipped car could begin using it immediately, without having to wait for enough automated vehicles to be sold to justify having their own lane. The downside, of course, is the technical difficulty of driving in mixed traffic. The automated vehicles would have to be safeguarded against all the bizarre variations of human driving styles now encountered on the road.

Our group at CMU is most interested in investigating the feasibility of mixed traffic.[1] While the problems are difficult, the payoff for success would be large; and the kinds of questions that need to be addressed are important and interesting from a research standpoint. Even if the ultimate completely automated system does not become practical in the near term, the technology developed could play an important role in improving safety of partially-automated vehicles in the immediate future.

We are investigating mixed traffic feasibility on several fronts: building partially-capable demonstration systems; building vehicle sensors; developing car detection and tracking strategies; developing capabilities for tactical driving; and planning future development steps.

CMU Demo Vehicles

Some of the functionality of driving in mixed traffic has already been built for other purposes, and will be shown in August of 1997 at the NAHSC San Diego Demonstration. The 97 Demo is a congressionally-mandated "Proof of Technical Feasibility" for automated driving. Various members of the NAHSC will show a variety of capabilities, including both mixed traffic and dedicated lane driving as well as maintenance and inspection functions.

The part of the Demo to which CMU is contributing will emphasize independent sensing and decision making on board each vehicle, including the capability of driving in mixed traffic and also the ability to take advantage of communication with other intelligent vehicles in the vicinity. The demo scenario shows a mix of vehicles being driven manually, vehicles under full automated control, and partially-automated vehicles. The cars and buses will demonstrate lane departure warning and adaptive cruise control, as well as automated lane following, headway and speed maintenance, lane changing to pass slower vehicles, and obstacle detection and avoidance. When two automated vehicles are driving close to each other, they will communicate to share information about relative positions of themselves and of detected obstacles, so that the trailing vehicle can safely drive with a smaller gap behind the lead vehicle. When automated vehicles are driving mixed with non-automated vehicles, they will automatically increase the free space buffer around themselves in order to have time to see and react to events.

The technology underlying the CMU portion of the demo starts with RALPH, the vision-based road following system built by Pomerleau.[2] RALPH resamples a video image to create an overhead projection of the road. In the overhead image, RALPH tests several hypothesized road curvatures to find the arc that most closely follows the dominant contrast features. This way, RALPH takes advantage of not only the painted stripes, but also the pavement joints, the shoulder edge, and other features that run parallel to the road. Once RALPH finds the dominant curvature, it can look for lane boundaries and calculate the vehicle's lateral position in the lane. RALPH has accumulated over 25,000 km of road tests, including the "No Hands Across America" trip during the summer of 1995 during which it steered autonomously over 98% of the way from Washington DC to San Diego CA.

The demo vehicles are also equipped with forward-looking radar. The radars on the cars are provided by Delco Electronics. They are mechanically scanned in azimuth, to cover a 12 degree field of view. The radars provide range, bearing, and range rate to targets in front of the vehicles, and have integrated target tracking software to filter out spurious or inconsistent readings. Besides providing data to control separation from other vehicles, the radars are also capable of detecting obstacles that have enough radar reflectivity. The obstacles used for the 1997 Demo will be plastic construction barrels. In our initial tests, the radars have detected the barrels at up to 80 m, perhaps due to the reflective tape wrapped around the barrels.

The demo vehicles are also equipped with side and rear looking sensors. The most difficult sensing requirement is forward, because stationary obstacles on the roadway need to be detected at long ranges. Sideways sensing is relatively straightforward, and even rear-looking sensors for the demo scenarios need only have a range of a few tens of meters. Several sensors are currently being investigated for side and rear applications, including a variety of low-cost radars, ladars, and sonars. Side-looking sensors detect presence of a vehicle, but not velocity; relative speeds must be inferred by tracking a vehicle as it is seen by front-looking sensors, then side sensors, and finally rear-facing sensors. The vehicles are also equipped with GPS positioning for navigation and for reporting the positions of detected obstacles.

The vehicles being built for the 97 Demo bring the Navlab family of vehicles up to a total of 10. Navlab 1 is a Chevrolet van, now retired; Navlabs 2 and 4 are HMMWVs, mostly used for off-road driving research; Navlab 3 is a privately-owned Honda Accord, now returned to service as a non-automated car. Navlab 6 and 7 are a matched pair of Pontiac Bonnevilles, designed for the 1997 Demo; Navlabs 5 and 8 are minivans used for general experiments and driver warning studies; and Navlabs 9 and 10 are a pair of city busses, adapted for the 1997 Demo by CMU and K2T Inc.

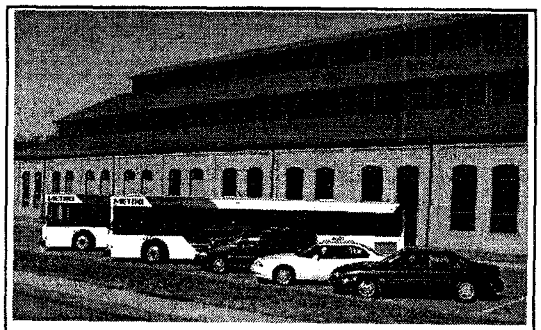

Figure 1: Navlabs 6 - 10, front to back

Vehicle Sensing

The Demo system described above provides partial solutions for driving in mixed traffic, but is not yet adequate for full tests in unconstrained situations. The first requirement is for better sensing.

Dirk Langer's thesis work, completed in January of 1997, is one part of our effort.[3] Langer built a phased-array radar that can cover a 12 degree field of view, with a range of 200 m, and does not use mechanical scanning. The specifications of the radar are:

- Range resolution: 0.6m
- Bearing resolution: 3 deg
- Range accuracy: 10 cm
- Bearing accuracy: 0.1 deg
- Repetition rate: 10 Hz

His software detects up to 20 radar targets in each measurement, and tracks those targets from measurement to measurement. The radar processing has been integrated with RALPH. The lane location and direction from RALPH are combined with the detected targets, to determine which targets are in the vehicle's lane and which are in adjacent lanes, even on curved roads. Similarly, the radar has also been integrated with GPS positioning and accurate maps to register targets with the next 100 meters of the road. This allows the radar to reject clutter such as guard rails or signs, while still properly detecting and reacting to stopped vehicles in the vehicle's own lane. The integrated systems have been demonstrated for a basic form of intelligent adaptive cruise control, and for detecting slow vehicles and triggering RALPH to change lanes.

Obstacle Sensing

Beyond sensing vehicles, it is also important to sense obstacles on the roadways. This may be the most difficult technical challenge for automated driving; it is certainly the most difficult sensing challenge.

Obstacle detection is especially important for mixed traffic scenarios. Many of the obstacles found today on roadways come from other vehicles: the dominant source of debris is tire carcasses and retreads, roughly followed by dead animals, spilled loads and dropped vehicle parts. (The dead animals were presumably alive when they wandered onto the roadway. In some parts of the rural US, the dominant cause of accidents is hitting deer). In dedicated lane configurations, some of these obstacles could be prevented by exercising more control over the roadway. Entering vehicles could be inspected for loose loads or fraying tires, and it may be possible (although expensive) to build fences along the dedicated lanes to prevent animals from wandering onto the roadway. Also, when one vehicle detects an obstacle, it would be expected to notify other nearby vehicles of the location and classification of the obstacle. Finally, if there are relatively few miles of dedicated lanes, it might be possible to install sensors in the infrastructure, and communicate obstacle locations and suggested avoidance strategies to the automated vehicles. These strategies raise issues of feasibility, liability, and cost, but they are technically plausible and are all under study in the NAHSC.

For driving in mixed traffic, most of the obstacle exclusion or infrastructure sensing strategies are not feasible. The first automated vehicles on the road would encounter today's driving environment, with the same issues of dropped loads, shed retreads, stray deer, and so forth. Since other vehicles would not be automated, no particular help could be expected in finding and avoiding obstacles; although locations with particularly dangerous roadway configurations may need to be equipped with infrastructure-based sensors that could provide warning of obstacles around a corner.

Within the NAHSC, the first part of the work on obstacle detection is cataloguing the kinds of obstacles that are present. Some of this data is available from maintenance departments of state departments of transportation, and some is in the accident literature, but none of it has been carefully quantified. The second part of the problem is determining which of those objects are dangerous. Our colleagues at General Motors are conducting informal experiments to understand the effect on a vehicle caused by running over various objects. The vehicle may ride smoothly over the object, or the object may cause ride discomfort, or steering deflection, or structural damage. The next part will be to write careful specifications for obstacle detection sensing. Some parts of the specification are straightforward to calculate. The maximum range for obstacle detection is set by the stopping distance of typical vehicles. In the worst case the obstacle, roadway configuration, and adjacent traffic will conspire to prevent a lane change to avoid the obstacle, so the only possible maneuver will be to come to a complete halt. Other parts of the spec are much more troublesome. It would be convenient to define a radar cross-section for a typical obstacle, but while some objects have large radar cross-sections (mufflers, steel-belted tire carcasses), others do not (wooden debris or deer).

At CMU we have started investigating possible obstacle detection methods even before the specifications are ready. One of the most promising approaches is using the reflectance channel of a ladar, being investigated by John Hancock as part of his thesis work. At the ranges of interest for obstacle detection (50 to 100 m), it is hard to generate a 3-D reconstruction of the roadway with enough accuracy to detect small objects (10 to 20 cm high). It may be more fruitful to look for changes in the reflectance of a patch of the road. Even if the range is nearly the same as the ranges to the road plane, an object sticking up from the road will have a much lower viewing angle than the roadway, and will therefore reflect much more of the laser energy. Preliminary results are shown in Figure 2. A small object, in this case a chunk of wood approximately 10 cm high by 50 cm long, does not show up in the range data. In the reflectance channel, however, it is easily noticeable, and simple processing to extract different-looking patches from the road area easily finds the object.

We are investigating philosophically similar approaches for stereo processing. We have a real-time stereo machine, capable of generating 256 * 240 pixel depth maps at 30 Hz, using up to 6 input cameras. This means that standard stereo processing to find obstacles is possible in real time. But roadways are typically

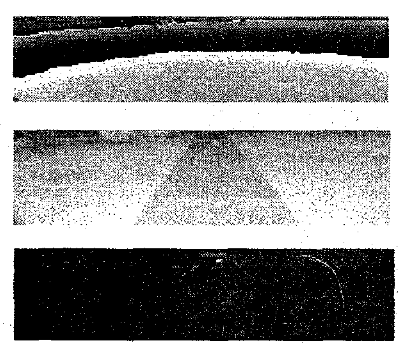

Figure 2: Obstacle Detection with Ladar Reflectance Top: range image. Middle: reflectance image, with obstacle near top of road. Bottom: Detected obstacle

bland, without enough texture to generate high-confidence depth maps. Todd Williamson and John Hancock, as part of their thesis projects, are studying ways of detecting obstacles against bland surfaces. Part of the approach is based on confidence measures, such as those pioneered by Matthies.[4] If an image patch from the reference image matches all other images at some disparity with low error, then either the image patch is very bland or the patch is planar. If the image patch matches with high error, then the patch is probably both textured and non-planar. By making the windows to be matched large enough to cover both a road marking and a suspected obstacle location, it should be possible to detect objects by looking at the matching error. Again, as in the case of ladar reflectance processing, the presence of an obstacle would be sensed even without first doing a complete 3D reconstruction.

An additional observation is that stereo processing is normally set up to look for surfaces that are parallel to the image plane. If the cameras are all parallel and co-planar, then a rectangular window from one image matched against a rectangular window in another image at a given disparity implicitly defines a surface parallel to the images. We use an alternative approach, based on the projective stereo geometry popularized by Faugeras.[5] The CMU Stereo Machine has a lookup table for each pixel for each disparity. Using projective stereo calibration, the lookup tables can be set up to interpolate between any two given planes. By calibrating the stereo system with a ground plane and a higher plane, parallel to the ground plane (in practice, the surface of a campus loading dock), the disparity of each pixel in a source window is automatically indexed to match horizontal surfaces in the target images. This effectively skews the matching window so that a horizontal surface in the source image will be correctly registered with a horizontal surface in the target images. This should provide better results, since most of the world in front of the vehicle is nearly horizontal.

Car Tracking

Besides detecting obstacles, the ladar and stereo vision sensors can also be used for fine-resolution car tracking. Radar is good for detecting vehicles and reporting their velocity, but does not have fine enough resolution to generate a vehicle image. With ladar, the pixels are small enough, and closely enough spaced, that it is possible both to localize a vehicle within a lane, and to measure the orientation of the vehicle. Since cars steer non-holonomically, the vehicle orientation is an important cue of imminent lane changes.

The sensor we are using for these experiments is a scanning laser rangefinder built jointly by CMU and K2T Inc. The laser points up through the middle of the scan mechanism. The mirror is spun horizontally, and nodded vertically, providing 360 degree horizontal coverage and up to 35 degrees vertical field of view. Various laser rangefinders have been installed in the device, including a Riegel sensor with a 120 m range and 5 cm resolution. A new range sensor, built by Zoeller und Froehlich GmbH, will be installed shortly, and will have a pixel rate of up to 500 kHz.

The images in Figure 3 show range data from a car parked inside a building, processed by Liang Zhao. The data is first thresholded by elevation, to give just the data between 50 and 150 cm from the ground. The region where the car is expected is then processed to find straight lines, and finally the lines are fit to a model of the expected car shape. We are currently testing how much data needs to be collected on a car in order to do accurate localization. We will then build Kalman filters to integrate data taken from several scans as the vehicles move.

Tactical Driving

Most of the discussion to this point has been about sensing: how to see the road, see vehicles, detect obstacles, and track the course of other cars. Once the environment of the vehicle has been sensed, there still remain difficult and interesting problems in planning and acting.

Much of the automated vehicle literature has focused on the low-level problems of smooth control, or on problems of route planning and guidance. There remains a hole in between these levels, which we call tactical reasoning. The tactical level, in this case, refers to decisions about when to change lanes, when to speed up or slow down, how to trade off caution with making adequate progress, and so forth. Our colleagues at PATH have worked extensively on tactical driving for platoons and dedicated

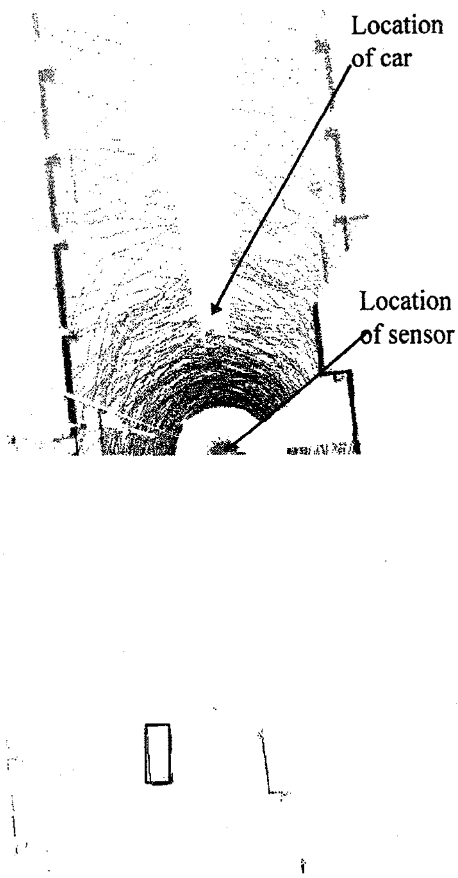

Figure 3: Car Tracking in ladar Images. Top: raw data. Bottom: data between height thresholds, and overlaid detected vehicle position

lanes[6,7], but there is still a large research gap in tactical driving in mixed traffic.

Rahul Sukthankar's recently completed thesis is a first step towards building safe and competent tactical driving in mixed traffic.[8,9] For obvious reasons, his research was conducted in the framework of a simulator. His system, called SAPIENT, evolved through two main stages.

MonoSAPIENT is a single-threaded rule-based driving system. It encodes rules for headway maintenance, speed keeping, and lane changing, based on vehicle plans and goals and on the physics of vehicle motion. Unfortunately, as the situations become more complex, MonoSAPIENT turns into a complex rule tree. Constructing those trees and ensuring correct ordering is difficult, as is ensuring that there are rules for each specific situation.

Partial solutions to these problems are developed in PolySAPIENT. Instead of a single set of rules, PolySAPIENT provides a separate "reasoning object" for each physical or logical object in the environment. Thus, each nearby car will have a reasoning object that keeps track of that vehicle, and the separation and relative velocity between that vehicle and the automated vehicle. Separate reasoning objects track lanes, exits, and internal parameters such as desired speed. Each reasoning object, at each time step, generates votes for desired actions and against bad actions, where the actions include both speed and turn commands. A knowledge-free arbiter selects the best action by a weighted combination of all votes.

While in MonoSAPIENT the rules are binary ("do not pass if ..."), in PolySAPIENT the individual reasoning objects can cast graded votes for and against actions. The result is that if several reasoning objects vote strongly for an action, and one or two reasoning objects vote weakly against it, the vehicle can choose that action. Thus PolySAPIENT vehicles are willing to squeeze into slightly tighter spaces than MonoSAPIENT vehicles, with a small sacrifice in desired headway, in order to move to a faster travel lane or to make a required exit.

Tuning all the relative weights of votes from all the reasoning objects and setting internal parameters is a difficult process. Fortunately, the tuning process can be automated. Sukthankar expressed the weights and parameters to be tuned as a string of bits, then used PBIL, an evolutionary algorithm, to tune the weights and parameters.[10] Simulated vehicles are generated with their weights and parameters set probabilistically according to the current bit string. The vehicles are run through a series of simulated scenarios, and are rated according to criteria such as avoiding near misses, arriving at their desired exits, and making adequate progress. The bit string is updated to more closely resemble the highly ranked vehicles, and the process repeats. After approximately 20 generations, the vehicles learn to drive smoothly and safely.

Next Steps

The individual components of our research are all coming together. The vehicles and the core road following will be demonstrated in

August 97; radars are becoming available and functional; obstacle detection is progressing; and the rules for tactical driving are running well in simulation. The various components are also being integrated: our demo vehicles will have multiple sensors, plus software for tracking other vehicles and the lane.

Once we are happy with sensing, we can begin testing the SAPIENT driving strategies. At least at first, we will have SAPIENT generate recommendations, and watch to see if we drive the way it would drive. Later, we can have SAPIENT generate recommendations via a head-up display or speech synthesizer, so we can determine if the recommendations are safe and reasonable. If SAPIENT's advice does not follow our driving patterns, then a variant of the learning methods used in PolySAPIENT could be used to tune the weights to better match our own preferred driving styles. Once we are happy with the way the system works, we might enable SAPIENT control in stages, first giving it longitudinal control, then lateral control within a lane, then lane-changing abilities. Throughout, we have designed our systems to have easily-accessible kill switches and low-powered actuators so the safety driver can always override the automated control.

Acknowledgments

The Concepts work, within the Consortium, is the part of the project studying design tradeoffs, including mixed traffic vs. dedicated lanes. The first phase of the Concept work was led by Jim Lewis of Hughes, the second phase by Steve Schladover of PATH, and the third phase is being run by Steve Carlton of Lockheed Martin. This paper reflects a CMU approach; our colleagues are developing other approaches, and we are jointly evaluating the various ideas.

The CMU AHS group is Parag Batavia, Michelle Bayouth, Frank Dellaert, Dave Duggins, John Hancock, Martial Hebert, Todd Jochem, Katsumi Kimoto, Phil Koopman, John Kozar, Bala Kumar, Dirk Langer, Sue McNeil, Illah Nourbakhsh, Dean Pomerleau, Rahul Sukthankar, Toshi Suzuki, Todd Williamson, and Liang Zhao.

Funding for this work comes from the US Department of Transportation, agreement DTFH61-94-X-00001, "Automated Highway System". The ladar hardware was funded by the Ben Franklin of Pennsylvania Technology Partnership through contract 95W.CC005OR-2, and the first radar prototype by DARPA through TACOM in contracts DAAE07-90-C-R059 and DAAE07-96-C-S075, "CMU Autonomous Ground Vehicle".

References

[1] Bayouth, M., and Thorpe, C. "An AHS Concept Based on an Autonomous Vehicle Architecture", in Proceedings of 3rd Annual World Congress on Intelligent Transportation Systems, 1996.

[2] Pomerleau, D. and Jochem, J. (1996) Rapidly Adapting Machine Vision for Automated Vehicle Steering. IEEE Expert, Vol. 11, No. 2

[3] Langer, Dirk. "An Integrated MMW Radar System for Outdoor Navigation", Carnegie Mellon University, Jan 1997

[4] Matthies, Larry. Stereo Vision for Planetary Rovers: Stochastic Modeling to Near Real-Time Implementation. International Journal of Computer Vision, 8:1, pp. 71-91, 1992.

[5] Faugeras, Olivier. Three-Dimensional Computer Vision: A Geometric Viewpoint. MIT Press, Cambridge, MA. 1993.

[6] Variya, Pravin. "Smart Cars on Smart Roads: Problems of Control", IEEE Transactions on Automatic Control, Vol. 38, No.2, Feb. 1993.

[7] Schladover, Steven. "Review of the State of Development of Advanced Vehicle Control Systems (AVCS)", Vehicle System Dynamics, Vol. 24, No. 6-7, Jul. 1995

[8] Sukthankar, Rahul. "Situational Awareness for Driving in Traffic", PhD thesis, Carnegie Mellon University, January 1997.

[9] Sukthankar, R., Hancock, J. and Thorpe, C. Tactical-level Simulation for Intelligent Transportation Systems. In Mathematical and Computer Modelling, Special Issue on Intelligent Transportation Systems, 1997.

[10] Baluja, S., Sukthankar, R., and Hancock, J. Prototyping Intelligent Vehicle Modules Using Evolutionary Algorithms. In D. Dasgupta and Z. Michalewicz, editors, to appear in "Evolutionary Algorithms in Engineering Applications", Springer-Verlag, 1997.